An Improved Local Binary Pattern Operator for Texture Classification

Fuxiang Lu[1], Jun Huang[2]

1. Lanzhou University

2. Shanghai Advanced Research Institute

Outline

- Introduction to Local Binary Pattern (LBP)
- Improved Local Binary Pattern (ILBP)
- Experiments
- Conclusion

Outline

- Introduction to Local Binary Pattern (LBP)
- Improved Local Binary Pattern (ILBP)
- Experimental results
- Conclusion

Three Questions

- What are Local Binary Pattern?
- Why should we care?
- Where can we use them?

What are Local Binary Pattern?

- Computationally efficient texture descriptor
  - Texture:
    - Variation of data at scales smaller than the scale of interest, or
    - Natural surfaces generally exhibit some repetitive gray-scale variations or patterns
  - Descriptor:
    - Compact representation that captures at least one essential characteristic of the sample under examination

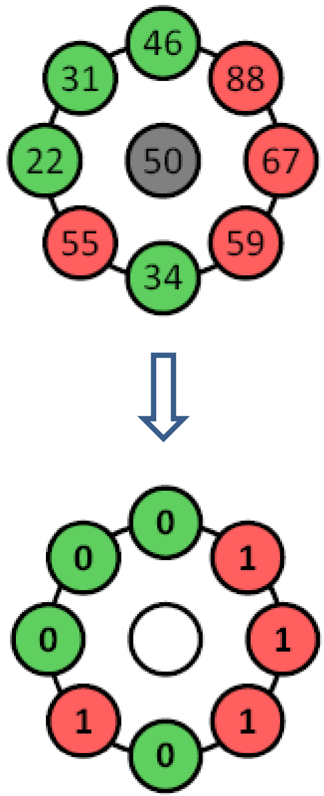
Why should we care?

- Rare technique that is good, fast and cheap
  - Good
    - Competitive with state-of-the-art for many image processing tasks
    - Robust to monotonic changes in illumination
  - Fast
    - O(n)
  - Cheap
    - No parameter tuning or image pre-processing required
    - Compact descriptor (good performance with < 64 element vector)

Where can we use LBP?

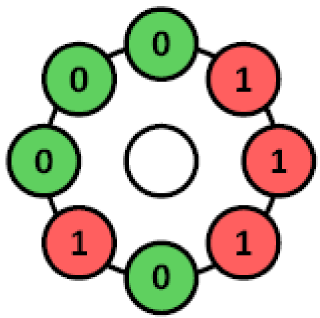
- Texture Analysis
  - Classification
  - Segmentation
  - Background Subtraction
  - Visual inspection
- Facial Analysis
  - Face Recognition
  - Face Detection
  - Expression Recognition
  - Gender Classification
- Image Analysis
  - Region Description
  - Image Forensics
  - Image Retrieval
  - Biometrics
- Motion Analysis
  - Gesture Recognition
  - Lip Reading
  - Object Detection
  - Gaze Tracking

Original LBP

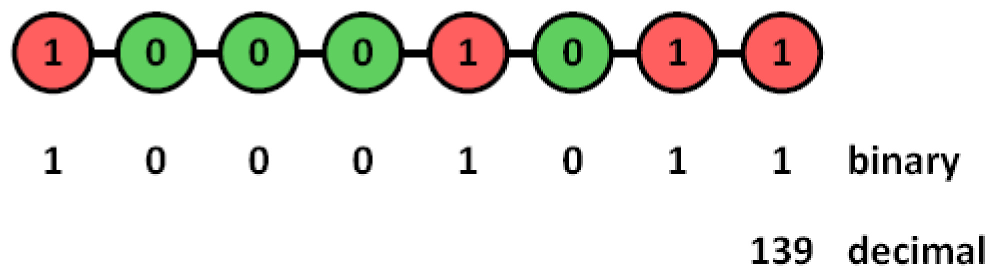


- Identify all pixels with luminance less than center pixel luminance
  - 22<50
  - 31<50
  - 34<50
  - 46<50
- Remaining pixels are greater than or equal to center pixel luminance
  - 55>50
  - 59>50
  - 67>50
  - 88>50
- Next, binarize results

Original LBP



- Finally, unroll the circular pattern to get LBP label

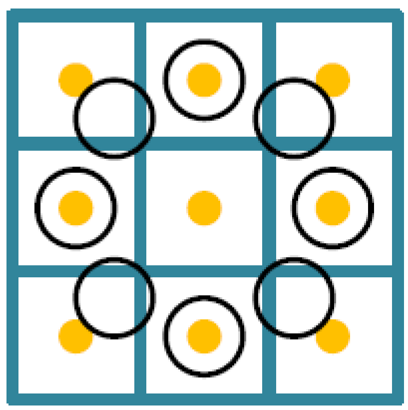


Original LBP

- Invariant to global illumination change
- Invariant to local contrast magnitude
- Capture gradient sign which describes the brighter/darker shape of the pattern
- Since contrast is orthogonal, it can be an effective additional feature in some cases

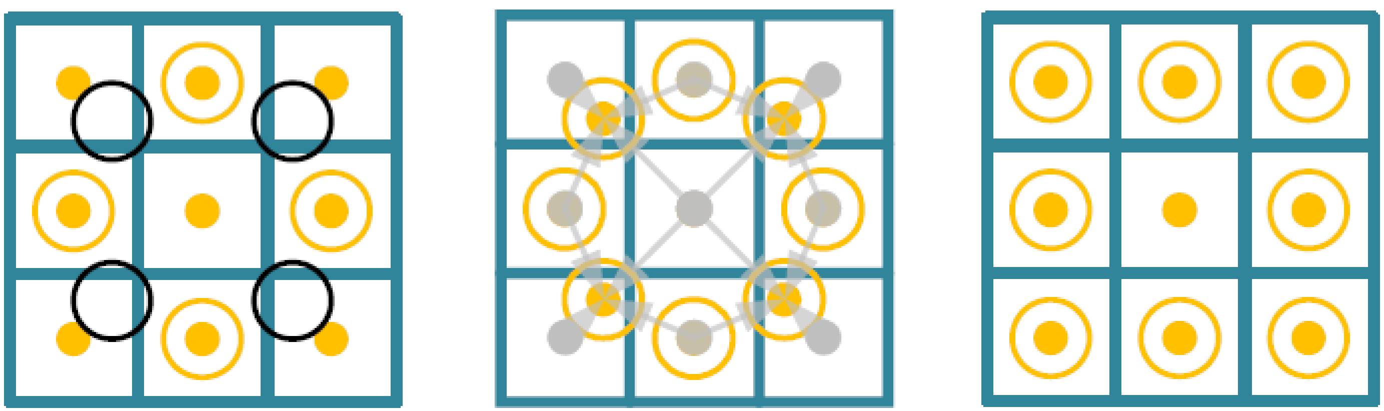
Original LBP

- For implementation, circular pattern doesn't fit standard square sampling grid very well.



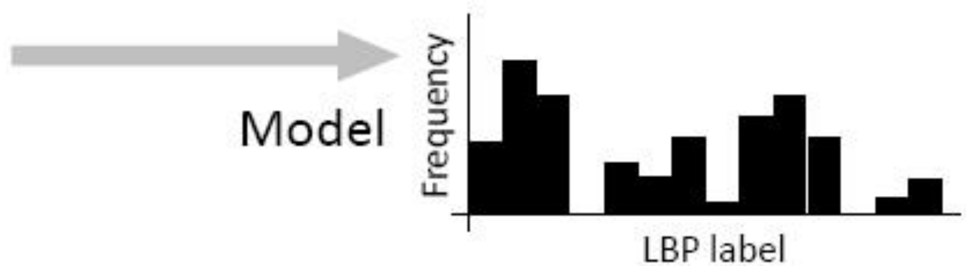
Original LBP

- On-grid points use sample data directly
- Off-grid points use interpolation
- Nearest Neighbor is often sufficient

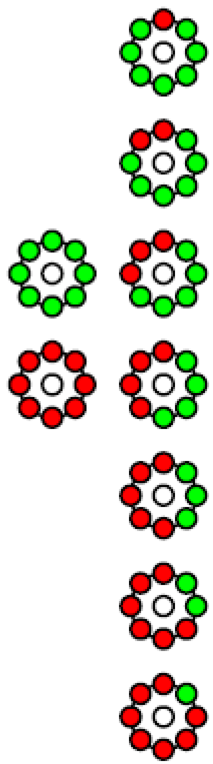


Original LBP

- After the LBP label/code of each pixel (except pixels on the boundary) in an image, a histogram of such LBP codes is commonly used for further analysis of the image



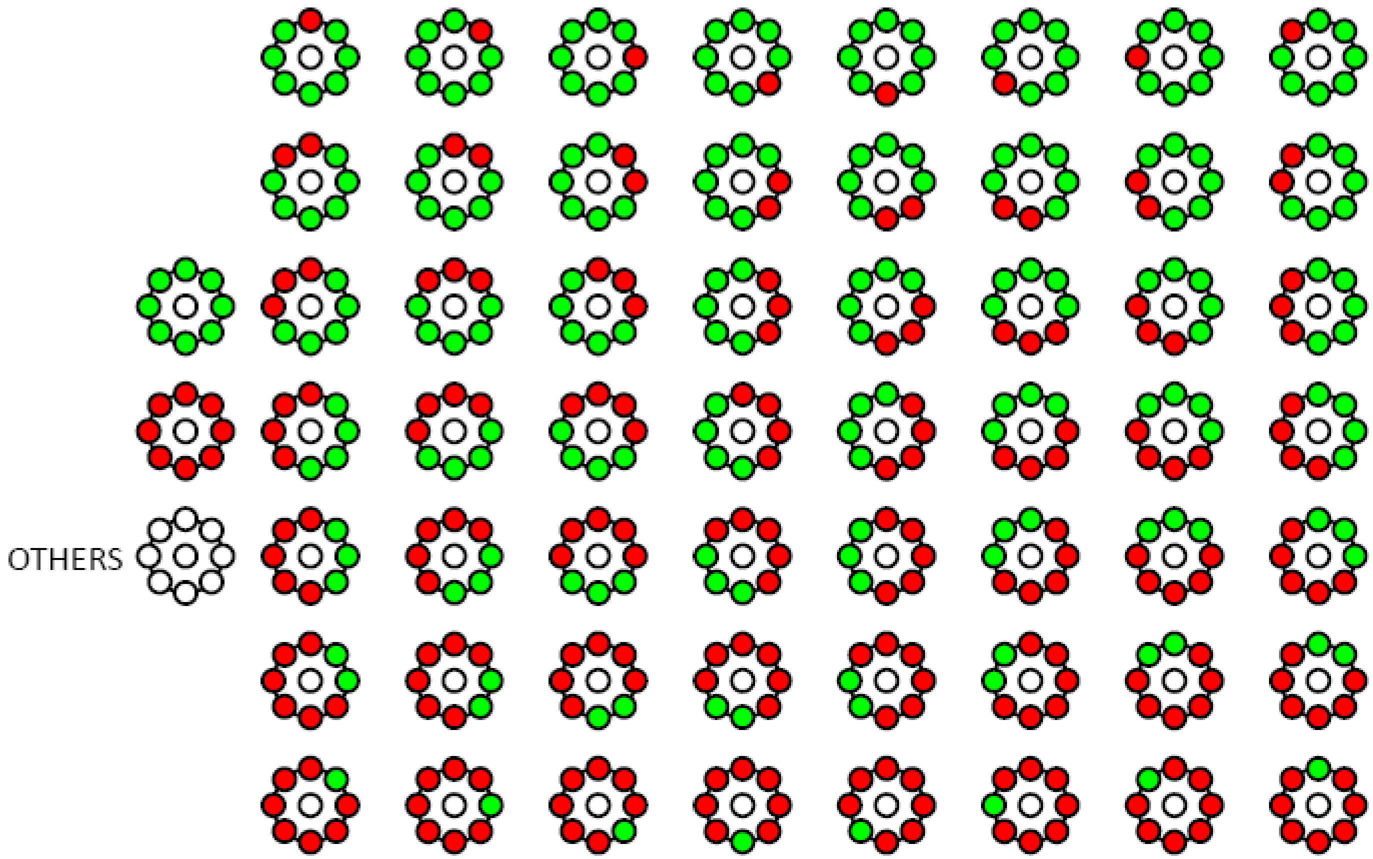
Uniform Local Binary Patterns



- Patterns with at most two contiguous regions
  - Two patterns with one contiguous region
  - Seven basic patterns with two contiguous regions
  - Each basic pattern has eight orientations

Uniform Local Binary Patterns

- 58 Uniform Local Binary Patterns plus one



Uniform Local Binary Patterns

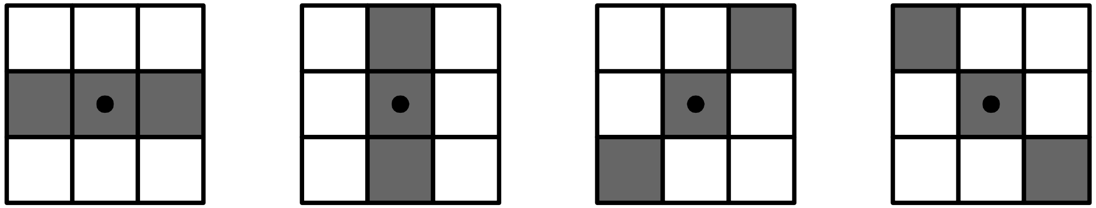
- Reduce feature vector from 256 to 59 elements
  - Helps with curse of dimensionality
- Natural images are ≈90% Uniform LBP
- Statistically more robust
  - Produce better recognition in many applications
  - Non-uniform patterns may not be robust to noise

Outline

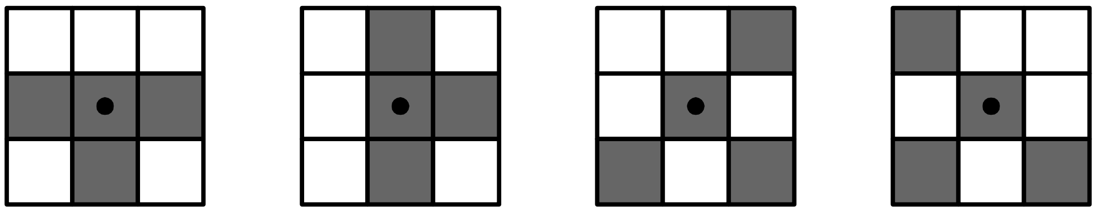
- Introduction to Local Binary Pattern (LBP)
- Improved Local Binary Pattern (ILBP)
- Experimental results
- Conclusion

Two observations

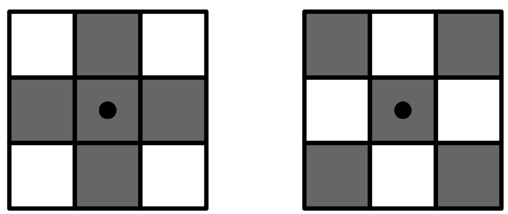
- Non-uniform local binary patterns account for more and more percent of all patterns as the size of the neighborhood increases.
  - 12.8% for the (8,1) neighborhood
  - 33.1% for the (16,2) neighborhood
  - 50.7% for the (24,3) neighborhood
- Some non-uniform patterns represent an important group of basic primitives that may be crucial for recognitions tasks.



Lines $\left(U = 4\right)$



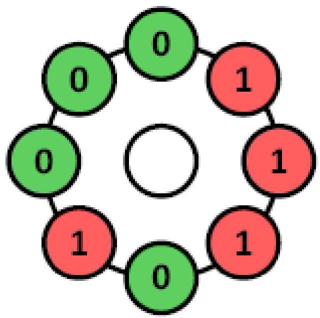
T-junctions $\left(U = 6\right)$



Cross intersections $\left(U = 8\right)$

Some basic primitives represented by non-uniform patterns. Here, White and gray rectangles correspond to bit values of 0 and 1 in binary patterns.

Improved Local Binary Patterns



$U = 4$

- A bitwise transition from 0 to 1 in the circular representation of the LBP code always accompanies a bitwise transition from 1 to 0 and vice versa.
- The uniformity value $U(LBP_{P,R})$ of an LBP code can only take an even number between 0 to P, because it corresponds to the number of spatial transitions in the LBP code if the LBP code is considered as circular.

Improved Local Binary Patterns

The uniformity measure of an LBP code is defined as follows:

$$U\left(LBP_{P,R}\right)=\sum_{p=0}^{P-1}\left|s\left(g_{p+1 \bmod P}-g_c\right)-s\left(g_p-g_c\right)\right|$$

where g_c is the intensity value of the center pixel, g_p is the intensity value of the p-th neighbor, $s(\cdot)$ is the sign function, and

$$LBP_{P,R}=\sum_{p=0}^{P-1} s\left(g_p-g_c\right)2^p$$

Improved Local Binary Patterns

- Motivations:
  - Extract information not only from uniform patterns but also from non-uniform patterns
  - Keep the resulting feature vector as compact as possible
- Implementation
  - Assign every pattern with $U \leq 2$ to a separate label
  - Divide patterns with $U > 2$ into several categories according to values of U, and all patterns from each category is assigned to a separate label.

Improved Local Binary Patterns

- To achieve rotation invariant, a locally rotation invariant ILBP is defined as follows:

$$ILBP_{P,R}^{ri} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), & U(LBP_{P,R}) \leq 2 \\ P - 1 + \frac{U}{2}, & U(LBP_{P,R}) > 2 \end{cases}$$

Improved Local Binary Patterns

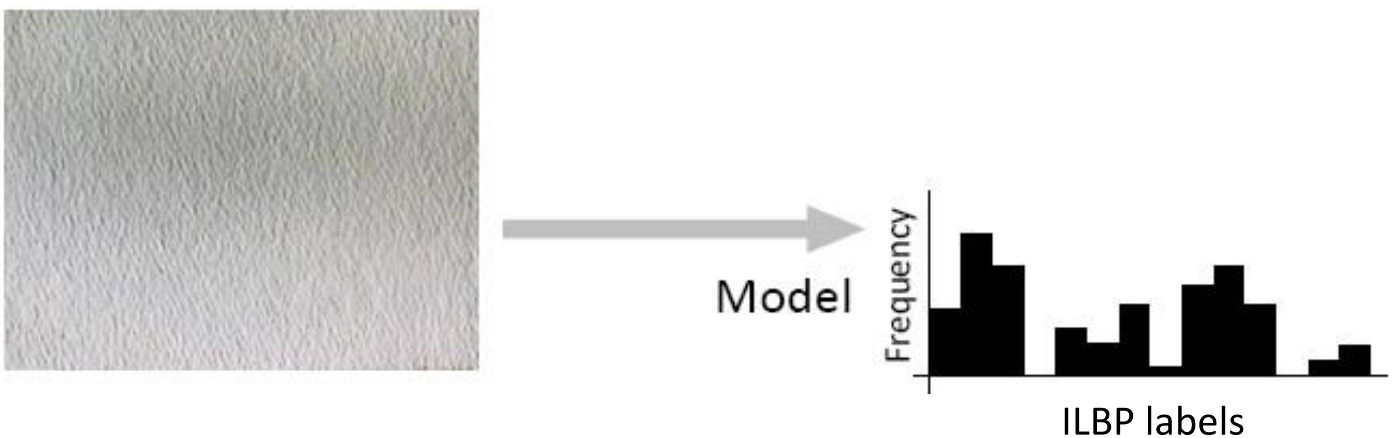
- Comparisons
  - Both $ILBP_{P,R}^{ri}$ and $LBP_{P,R}^{u2}$ are invariant in terms of monotonic gray-scale variation and rotation transformation.
  - $LBP_{P,R}^{u2}$ assigns all non-uniform patterns to a "miscellaneous" label, whereas $ILBP_{P,R}^{ri}$ assigns them to different labels according to their uniformity values.
  - $ILBP_{P,R}^{ri}$ is more descriptive than $LBP_{P,R}^{u2}$ because $ILBP_{P,R}$ discovers an important group of local primitives such as lines, T-junctions and cross intersections, which are ignored by $LBP_{P,R}^{u2}$.

Outline

- Introduction to Local Binary Pattern (LBP)
- Improved Local Binary Pattern (ILBP)
- Experimental results
- Conclusion

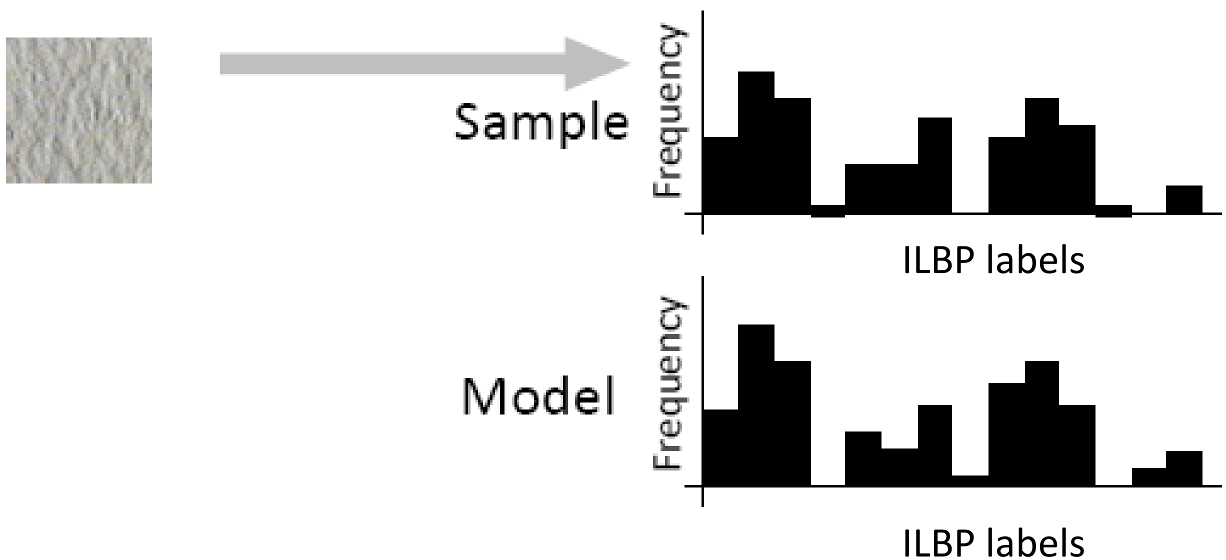
Texture Classification: Training

- Calculate ILBP for every pixel in exemplar
- Histogram is model of micro-textures in exemplar



Texture classification: Recognition

- Create ILBP histogram from sample
- Find distance between sample & model histograms



- A testing sample is assigned to the class of the model with minimum distance.

Texture classification: Recognition

- Three commonly used distance measures
  - G-statistic

$$G(S,M) = -\sum_{b=1}^{B} s_b \log(s_b + m_b)$$

  - Histogram intersection

$$H(S,M) = -\sum_{b=1}^{B} \min(s_b, m_b\,)$$

  - Chi-Squared

$$\chi^2(S,M) = \sum_{b=1}^{B} \frac{(s_b - m_b)^2}{s_b + m_b}$$

Experiments on RotInv_16_10

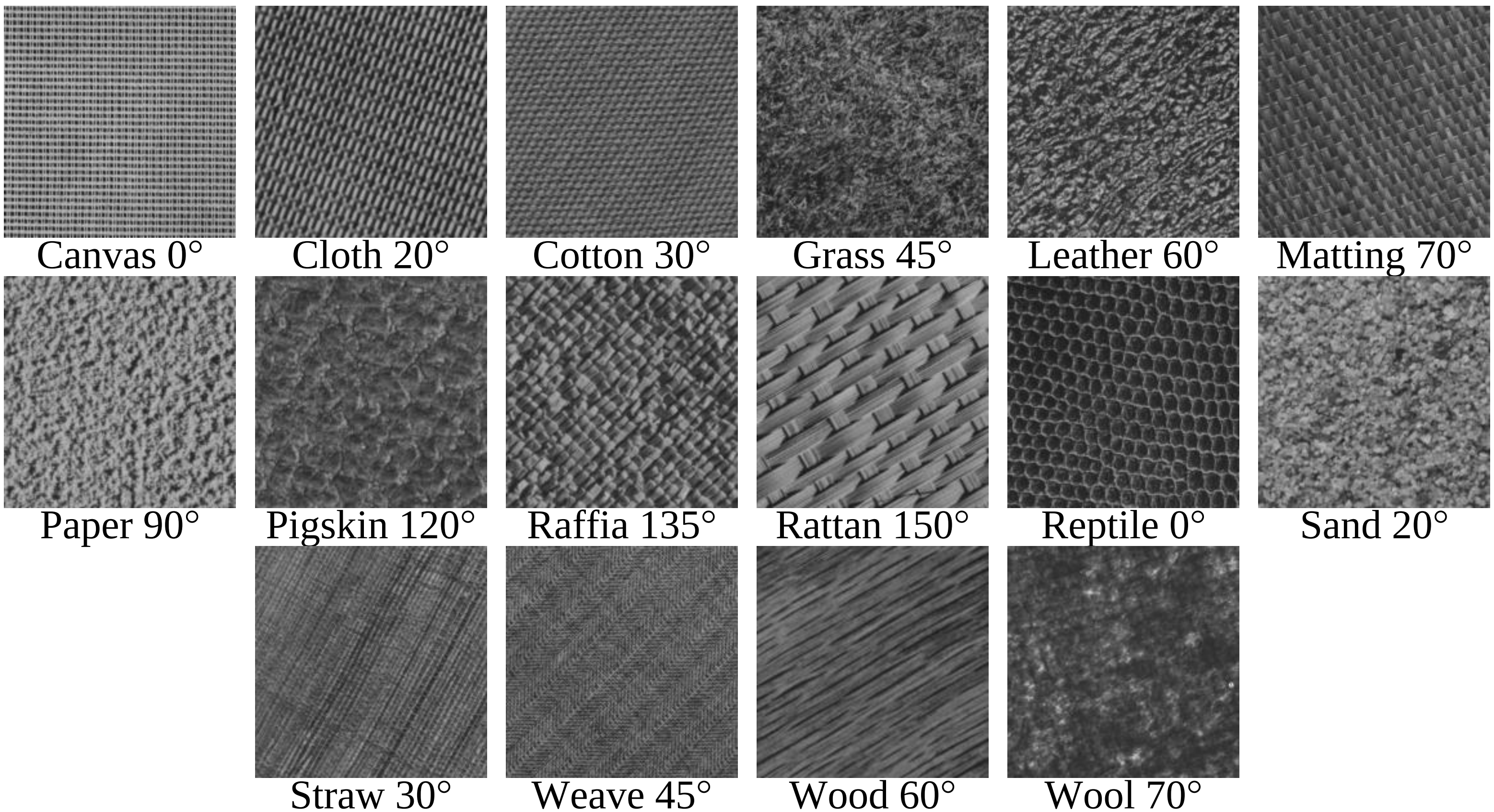
- RotInv_16_10
  - Type of problem
    - Rotation-invariant texture classification
  - Number of texture classes
    - 16 textures from the Brodatz album
  - Rotation angles
    - $0^{\circ}, 20^{\circ}, 30^{\circ}, 45^{\circ}, 60^{\circ}, 70^{\circ}, 90^{\circ}, 120^{\circ}, 135^{\circ}$, and 150°
  - Image size
    - 16x16 pixels (training images), 180x180 pixels (testing images)
  - Number of images (samples)
    - 121 training images for each class and angle
    - 7 testing images for each class and angle
  - Pixel format
    - 8-bit monochrome

Experiments on RotInv_16_10

- Experimental setup
  - The experiments are represented ten times.
  - For each run, the 16×16 samples of just one rotation angle are used as training data and the samples of the other nine rotation angles are used as testing data.
  - This setup is a true test for different LBP operators' ability to produce a rotation invariant description of local region.

Experiments on RotInv_16_10

- Samples from RotInv_16_10



Experiments on RotInv_16_10

Table 1. Classification accuracies (%) on RotInv_16_10.

Training angle	$LBP_{P,R}^{riu2}$ (8,1)	(16,2)	(24,3)	$ILBP_{P,R}^{ri}$ (8,1)	(16,2)	(24,3)
0°	68.2	96.2	98.7	67.8	97.6	97.6
20°	86.1	99.0	98.9	86.3	99.9	99.9
30°	84.7	98.7	99.1	85.3	99.7	99.4
45°	76.1	99.1	97.6	76.6	99.6	99.4
60°	84.7	98.3	99.2	85.0	98.4	98.6
70°	84.2	99.1	98.2	84.6	99.7	98.2
90°	69.3	97.6	100.0	68.1	97.8	99.5
120°	84.4	98.6	98.6	85.4	99.5	99.4
135°	76.0	98.6	96.7	76.2	98.9	97.5
150°	84.4	97.7	98.0	85.0	98.8	99.2
Mean	79.8	98.3	98.5	**80.0**	**99.0**	**98.9**

Experiments on Outex

- Outex
  - Comprise textural images from a wide variety of real materials
  - Provide some ready-made test suits to evaluate algorithms for various types of texture analysis
- Outex_TC_00010 (TC10)
  - To evaluate algorithms for *rotation invariant* texture classification
- Outex_TC_00012 (TC12)
  - To evaluate algorithms for rotation and illumination invariant texture classification

Experiments on Outex

- TC10 and TC12
  - Number of texture classes
    - 24 textures
  - Rotation angles
    - $0^{\circ}, 5^{\circ}, 10^{\circ}, 15^{\circ}, 30^{\circ}, 45^{\circ}, 60^{\circ}, 75^{\circ}$, and 90°
  - Image size
    - 128×128 pixels
  - Number of images
    - 20 images for each illumination and rotation angle in each class
  - Illumination
    - “horizon”, “inca” and “tl84”

Experiments on Outex

- Experimental setups
  - TC10
    - 20 samples in each texture class with illumination “inca” and 0° angle are served as training data, and 160 samples in each class with the same illumination but the other 8 rotation angles are reserved as testing data
  - TC12
    - The classifiers are trained with the same training samples as TC10 but tested twice with all samples captured using the other two illumination conditions.

Experiments on Outex

- Experimental results

Table 2. Classification accuracies (%) on TC10 and TC12.

	$LBP_{P,R}^{riu2}$			$ILBP_{P,R}^{ri}$		
(P, R)	TC10	TC12		TC10	TC12	
		'tl84'	'horizon'		'tl84'	'horizon'
$(8, 1)$	84.2	65.0	63.7	**85.4**	**66.4**	**65.1**
$(16, 2)$	89.4	82.4	75.6	**91.7**	**83.5**	**78.7**
$(24, 3)$	95.3	85.2	81.3	**96.3**	**86.3**	81.3

Outline

- Introduction to Local Binary Pattern (LBP)
- Improved Local Binary Pattern (ILBP)
- Experimental results
- Conclusion

Conclusion

- The ILBP operator detects an important group of local primitives from non-uniform patterns and thus the ILBP feature has more powerful discriminative ability than traditional LBP ones.
- The ILBP feature is invariant in terms of monotonic gray-scale change and rotation transformation.
- The ILBP is computationally attractive and well suited for real-word applications because it can be realized with a few operators and a look-up table.

Discussion

- Similar to the LBP operator, the ILBP operator is sensitive to noise and small pixel value fluctuations.
- A possible research direction is to encode the small gray value difference into a third state according to a threshold as that in LTP (Local Ternary Pattern), but the resulting operator is no longer invariant to illumination change and rotation transformation.
- Our future work is to find a compact ILBP-based feature which can achieve a better tradeoff between the discriminative power and robustness.

- Thank you!